Daily physical activity assessment with accelerometers: new insights and validation studies.

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Daily physical activity assessment with accelerometers: new insights and validation studies

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Summary

The field of application of accelerometry is diverse and ever expanding. Because by definition all physical activities lead to energy expenditure, the doubly labelled water (DLW) method as gold standard to assess total energy expenditure over longer periods of time is the method of choice to validate accelerometers in their ability to assess daily physical activities. The aim of this paper was to provide a systematic overview of all recent (2007–2011) accelerometer validation studies using DLW as the reference. The PubMed Central database was searched using the following keywords: doubly or double labelled or labeled water in combination with accelerometer, accelerometry, motion sensor, or activity monitor. Limits were set to include articles from 2007 to 2011, as earlier publications were covered in a previous review. In total, 38 articles were identified, of which 25 were selected to contain sufficient new data. Eighteen different accelerometers were validated. There was a large variability in accelerometer output and their validity to assess daily physical activity. Activity type recognition has great potential to improve the assessment of physical activity-related health outcomes. So far, there is little evidence that adding other physiological measures such as heart rate significantly improves the estimation of energy expenditure.

Keywords: Accelerometry, activity monitor, doubly labelled water, motion sensor.

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Introduction

Given the importance of regular physical activity in maintaining health, the quest for valid methodologies to measure physical activities under the unconfined conditions of daily life is ever expanding. Activity monitors or accelerometers can objectively capture body movement and provide information on the total amount, intensity, duration and frequency of physical activities performed. As a consequence, applying accelerometry as a tool to assess daily physical activities is a rapidly evolving field of research. Early piezo-resistive accelerometers that were able to capture static acceleration such as the gravitational field were hampered by a large battery unit and limited battery life (1). Many motion sensors therefore switched from piezo-resistive to piezoelectric accelerometers, which required less battery power and hence were considerably smaller in size and allowed data capturing over longer periods of time up to 3 weeks (2). Over recent years, a particular interest has occurred in capturing not only body movement but also the type of activity performed. The importance of activity recognition is supported by epidemiological data showing that sedentary behaviour is a risk factor for diseases, independent of the level of physical activity (3,4). Those findings generated the need to objectively assess postures and therefore modern piezo-resistive and capacitive accelerometers that combine the advantage of measuring the gravitational field along with small size and weight and long battery life have been developed. Measuring the gravitational field allows to determine the orientation of the body and consequently body posture. In order to measure the type of physical activity, there is also a need to capture body movement at a high frequency and to store raw unprocessed data. The memory capacity of most accelerometers has evolved equally rapid allowing the collection of raw acceleration data (e.g. at 30–100 Hz) over several weeks.

The definition of physical activity provided by Caspersen *et al*. states that physical activity comprises any body movement, produced by skeletal muscles, that results in energy expenditure (EE) (5). Indeed, the laws of physics dictate that energy is required to perform (mechanical) work. The direct consequence is that body movement, as assessed by an accelerometer, should lead to an increase in EE, and a relation between accelerometer output and an independent measure of EE, such as doubly labelled water (DLW), should be present.

As shown earlier, many, although not all, accelerometers perform poorly when compared to the gold standard of DLW (6). Therefore, some researchers have attempted to increase the accuracy of activity monitors to assess activity-related EE by adding other physiological measures such as body temperature or heart rate (HR).

Given the large amount of activity monitors available, it has become a major challenge for researchers to keep up with the new developments in the field and to decide which device to use and why. This paper aims to summarize all recent literature on the validity of different accelerometers and to provide an overview of some technical characteristics of these accelerometers. Given the relation between body movement and EE, as dictated by the laws of physics, and the requisite that physical activity needs to be measured under unconfined conditions, DLW-assessed EE was chosen as the reference technique.

Methods

The PubMed Central database (U.S. National Institutes of Health free digital archive of biomedical and life sciences journal literature) was searched using the following keywords: doubly or double labelled or labeled water in combination with accelerometer, accelerometry, motion sensor or activity monitor. Limits were set to include articles published between January 2007 and December 2011. Studies published before 2007 have been covered in a previous review (6). In total, 38 articles were identified of which 25 contained new data on the validity of the accelerometer as compared to DLW. Thirteen articles were not included because no new data were included (e.g. review article) or no comparison was made between accelerometry and DLW (6–18).

Results

Eighteen different accelerometers from 15 different brands were identified (Table 1). For the Actigraph (Actigraph, Pensacola, FL, USA), SenseWear (BodyMedia, Inc., Pittsburgh, PA, USA) and Tracmor (Philips New Wellness Solutions, Eindhoven, the Netherlands), two different versions of the accelerometer were validated. Five out of the 18 monitors were included and briefly described in a previous review (6). The remaining activity monitors that have been validated in daily life over the past 5 years are briefly described below. Table 1 provides an overview of all validated accelerometers with details about the number of axes, wearing position, size, weight, sampling frequency, frequency response and dynamic range, when provided. Data about the accelerometer were retrieved from the validation study included in Table 2 and from additional literature and company websites when available. The results in Table 1 show that only few companies provide information about the frequency response and dynamic range of the accelerometer.

Description of accelerometers

The 3dNX™ (BioTel Ltd, Bristol, UK) is a triaxial accelerometer weighing 93 g including the battery. It contains three piezoelectric ADXL210E sensors (Analog Devices, Surrey, UK) (19). The Accusplit AX120 is a hip-worn spring-lever pedometer (Accusplit, San Jose, CA, USA). The Dynastream AMP-331 is a triaxial accelerometer (Cochrane, Alberta, Canada) positioned on the back of the ankle which measures the forward and vertical accelerations to determine the position of the foot in space (20,21). The Actiheart (Cambridge Neurotechnology Ltd, Cambridge, UK) is a combined HR and movement sensor. The main component is 7 mm thick with a diameter of 33 mm and houses a movement sensor, a rechargeable battery, a memory chip and other electronics. A wire of approximately 100 mm length runs to a smaller (5 × 11 × 22 mm) clip. An 8-min step test at a step height of 20 cm is used to provide individual calibration of HR to physical activity intensity (22,23). The SenseWear Pro Armband (BodyMedia, Inc., Pittsburgh, PA, USA) is a multiple sensor device collecting data from a skin temperature sensor, near-body temperature sensor, heat flux sensor, galvanic skin response sensor and a biaxial accelerometer. These signals are combined to assess the type and intensity of an activity. Together with information about gender, age, height and weight, EE is estimated. The SenseWear Mini (Model: MF-SW) is a newer and smaller version of the SenseWear Armband. The Mini operates in a similar manner but includes a three-axis accelerometer rather than a two-axis accelerometer (24,25). The ActivPAL (PAL Technologies Ltd, Glasgow, UK) uses a uniaxial accelerometer sampling at 10 Hz to produce signals reflecting thigh inclination and movement. The software classifies positions and activities into three categories: lying or sitting, standing and stepping. Cadence and number of steps taken describes the intensity and volume of activity. The software assigns each activity an estimated energy cost in metabolic equivalents (METs), which are then summated over the

Table 1 Technical specifications of the accelerometers that were validated against doubly labelled water

Name	Manufacturer	Number of axes	Type	Wearing position	Frequency response (Hz)	Sampling frequency (Hz)	Dynamic range (g)	Size (mm)	Weight (g)	Reference
3dNX	BioTel Ltd., Bristol, UK	3	Piezoelectric	Hip/lower back	0.2–10	100	±18	125 × 58 × 8	93	(19)
Accusplit AX-120	Accusplit, San Jose, CA, USA	1	Spring-lever pedometer	Waist						(20)
Actigraph (model 7164)	No longer available	1	Piezoelectric	Waist	0.25–2.5	10	0.05–2.0	51 × 41 × 15	43	(20,51–53)
Actigraph* (GT1M)	Actigraph, Pensacola, FL, USA (no longer available)	1	Capacitive	Waist	0.25–2.5	30	0.05–2.0	38 × 37 × 18	27	(34,35, 51,53,54)
Dynastream AMP-331	Dynastream Innovations Inc. Cochrane, Alberta, Canada	3	(No longer available)	Ankle						(20)
Actiheart	Cambridge Neurotechnology Ltd, Cambridge, UK	1 (also HR monitoring)	Piezoelectric	Chest	1–7	32	±2.5	7 × 33; 100-mm wire; 5 × 11 × 22	8	(22)
ActiReg	PreMed AS, Oslo, Norway	2 motion and 2 position sensors	All or none principle†	1 sensor at sternum, 1 at right thigh and storage unit at waist				85 × 45 × 15; cables	60	(24,55,56)
SenseWear Pro	BodyMedia, Inc., Pittsburgh, PA, USA	2 (also heat flux, skin temperature, galvanic skin response)		Upper arm over triceps				85 × 53 × 20	79	(25)
SenseWear Mini	BodyMedia, Inc., Pittsburgh, PA, USA	3 (also heat flux, skin temperature, galvanic skin response)		Upper arm over triceps				55 × 62 × 13	45	(25)
ActivPAL‡	PAL Technologies Ltd, Glasgow, UK	1	Capacitive	Thigh		10	0–1.5	35 × 53 × 7	15	(26)
GENEA	Unilever Discover, Sharnbrook, Bedfordshire, UK	3	(MEMS seismic)	Wrist and waist		10–80	±6	36 × 30 × 12	16	(27,57)

Table 1 *Continued*

Name	Manufacturer	Number of axes	Type	Wearing position	Frequency response (Hz)	Sampling frequency (Hz)	Dynamic range (g)	Size (mm)	Weight (g)	Reference
Lifecorder[§]	Suzuken Co. Ltd., Nagoya, Japan	1	Piezoelectric	Waist		32	0.06–1.94	62 × 46 × 26	42	(58,59)
IDEEA[¶]	Minisun, Fresno, CA, USA	5 × 2		2 at upper legs, 2 on feet, 1 on sternum				5 sensors, each 16 × 14 × 4; cables	200	(31,40)
New Lifestyles Pedometer NL-2000	New-Lifestyles, Inc., Lee's Summit, MO, USA	1	Piezoelectric	Waist						(28)
RT3**	Stayhealthy, Inc. Monrovia, CA, USA	3	Piezo-resistive	Waist				68 × 48 × 18	63	(29,30,36)
Tritrac	Reining Ltd., Madison, WI, USA[††]	3		Waist				120 × 65 × 22	168	(30)
Tracmor	Philips Research, Eindhoven, the Netherlands	3	Piezo-capacitive	Lower back		20		80 × 35 × 10	35	(42)
$Tracmor_D$	Philips New Wellness Solutions, Eindhoven, the Netherlands	3	Piezo-capacitive	Lower back				32 × 32 × 5	13	(32)

*Actigraph now has the Actigraph GT3X+ model available that is triaxial and allows user-defined data sampling at 30–100 Hz.
[†]The motion sensor only registers 'movement' or 'no movement'.
[‡]A triaxial version of the ActivPAL is also available (ActivPAL(3) ™).
[§]A maximum pulse over 4 s is taken as the acceleration value, and the activities are categorized into 11 activity levels (0.0, 0.5 and 1.0–9.0; level 0.0 corresponds to less than 0.06 g) based on the pattern of the accelerometric signal. The activity levels are subsequently converted by a proprietary algorithm to calculate energy expenditure (kcal) (58).
[¶]Five sets of sensors, attached by thin flexible cables to a 200-g data collection device, each sensor being able to measure angles of body segments and movements (acceleration) in two orthogonal directions.
**The acceleration is measured periodically, converted to a digital representation, and processed to obtain an activity count. This information is then converted by using the subject's characteristics (by unpublished proprietary equations) into energy estimates (30).
[††]Stayhealthy Inc. (Monrovia, CA) purchased the technology and rights to the Tritrac from Reining International. Then a smaller triaxial accelerometer was developed called the RT3 (60).
g, acceleration of gravity; HR, heart rate; IDEEA, Intelligent Device for Energy Expenditure and Physical Activity; MEMS, micro-electro-mechanical system.

Table 2 Overview of the results of all accelerometer validation studies against doubly labelled water

Subjects	Accelerometer	*N* days accelerometry	*N* days DLW	BMR (Measured or Calculated)	Dependent variable	Independent variables (non-significant variables included in the model are indicated with NS)	*R*	PR or RI	Difference DLW-accelerometer (mean ± 2 SD)	Ref
23 adolescents	3dNX	10	10	RMR_C	TEE	AC	0.52			(19)
						AC, BM, gender	0.79	NP		
						FFM, AC	0.88	0.40 (RI)		
14 young adults (trainee guardsmen)						AC	0.59			
						Height, AC	0.85	0.52 (RI)		
						FFM, AC	0.83	0.46 (RI)		
50 American Indians (20–34 years)	Accusplit-AX120	7	7	RMR_M	PAL_{adj}	$Steps_{AX120}$	0.34			(20)
						$Steps_{Actigraph}$	0.44			
	Actigraph (model 7164)				AEE	$Steps_{AMP}$	0.43			
	Dynastream-AMP					$Steps_{AX120}$	0.18			
						$Steps_{Actigraph}$	0.47			
						$Steps_{AMP}$	0.42			
85 children (5 years)	Actigraph	3–7	7–10	$RMR_{M\ or\ C}$	TEE (MJ d^{-1})	$TEE_{Ekelund\ eq}$			–0.3 ± 4.0	(61)
						$TEE_{Puyau\ eq.}$			0.3 ± 3.5	
58 Indian children (8–9 years)	Actigraph (models GT1M and 7164)	14	14	BMR_C	PAL	AC	0.17^{NS}			(53)
					TEE	AC	0.18^{NS}			
						$TEE_{Ekelund}$	0.33			
					AEE	AC	0.18^{NS}			
29 children (4–5 years)	Actigraph (model 7164)	11	11	RMR_M	AEE (kJ kg^{-1} d^{-1})	$MVPA_{>3,000}$	0.35^{NS}			(52)
						$MVPA_{>1,952}$	0.38			
27 children (12–13 years)						$MVPA_{>3,000}$	0.38^{NS}			
						$MVPA_{>1,952}$	0.29^{NS}			
26 children (16–17 years)						$MVPA_{>3,000}$	0.54			
						$MVPA_{>1,952}$	0.52			
33 free-living urban and rural dwellers in Cameroon	Actigraph GT1M	7	7	RMR_M	AEE (kJ kg^{-1} d^{-1})	AC	0.37		0.67 ± 60.14†	(34)
						AC, age, gender, %BF	0.59	NP	0.65 ± 57.32†	
						AC, age, gender, %BF, urban	0.63	NP	0.05 ± 57.25†	
30 adolescents, India	Actigraph GT1M	7	7	BMR_C	AEE (MJ d^{-1})	AC	0.30		0.01 ± 2.35†	(35)
						AC, FFM, gender	0.50	NP	–0.03 ± 2.34†	
						AC, BM, gender	0.30	NP	–0.01 ± 2.53†	
					AEE (kJ kgFFM d^{-1})	AC, gender	0.26	NP	0.03 ± 56.5†	
					AEE (kJ kg^{-1} d^{-1})	AC, gender	0.36	NP	0.05 ± 47.9†	
22 healthy adults	Actigraph GT1M	14	14	RMR_M	TEE (MET·min·d^{-1})	TEE (MET·min·d^{-1})	NP		–84 ± 684 (–6 ± 32%)	(54)
						TEE_{LPF} (MET·min·d^{-1})	NP		4 ± 672 (1.7 ± 31%)	
33 free-living urban and rural dwellers in Cameroon	Actiheart	7	7	RMR_M	AEE (kJ kg^{-1} d^{-1})	AEE $ACC{+}HR_{step}$	0.40		5.4 ± 57.3	(22)
						AEE $ACC{+}HR_{group}$	0.39		9.1 ± 56.7	
						AEE HR_{flex}	0.32^{NS}		–1.2 ± 70.1	
						AEE AC	0.54		26.6 ± 52.7	
60 normal and overweight 5–18 years old	Actiheart	7	7	BMR_M	TEE (MJ d^{-1})	TEE_{CSTS}	0.86^{CCC}		–0.04 ± 2.57	(62)
						TEE_{MARS}	0.91^{CCC}		–0.08 ± 2.11	
					AEE (MJ d^{-1})	AEE_{CSTS}			0.08 ± 1.91	
						AEE_{MARS}			0.00 ± 1.65	

Table 2 *Continued*

Subjects	Accelerometer	*N* days accelerometry	*N* days DLW	BMR (Measured or Calculated)	Dependent variable	Independent variables (non-significant variables included in the model are indicated with NS)	*R*	PR or RI	Difference DLW-accelerometer (mean ± 2 SD)	Ref
20 healthy children (14–15 years)	ActiReg	14	14	RMR$_M$	TEE (kJ kg^{-1} d^{-1})	TEE$_{\text{AR old}}$	0.69		−11 ± 50	(24)
						TEE$_{\text{AR new}}$	0.71		0 ± 44	
	SenseWear					TEE$_{\text{SWA 5.1}}$	0.79		−17 ± 40	
						TEE$_{\text{SWA 6.1}}$	0.74		10 ± 42	
15 patients total gastrectomy	ActiReg	3	14	BMR$_M$	TEE	TEE$_{\text{AR}}$ (MJ d^{-1})	0.89		0.75 ± 2.13	(55)
					PAL	PAL$_{\text{AR}}$	NP		0.15 ± NP	
6 cancer patients and 9 healthy controls	ActivPAL	14	14	RMR$_M$	AEE (MJ d^{-1})	Step count	0.89			(26)
						Time spent upright	0.72			
						AEE$_{\text{ActivPAL}}$			0.08 ± 2.93	
						TEE$_{\text{ActivPAL}}$			0.04 ± 3.33	
48 non-pregnant Swedish women	GENEA	7	10	RMR$_M$	AEE (MJ d^{-1})	AC	0.46			(57)
						AC, weight	0.56	NP		
						AC, body side^{NS}	0.42	NP		
26 pregnant Swedish women						AC	0.30^{NS}			
						AC, weight^{NS}	0.22^{NS}	NP		
						AC, body side	0.44^{NS}	NP		
18 pregnant Swedish women	IDEEA	3–	14	BMR$_M$	TEE (MJ d^{-1})	TEE$_{\text{IDEEA}}$	0.81		1.0 ± 2.2	(40)
					AEE (MJ d^{-1})	AEE$_{\text{IDEEA}}$	0.49			
21 non-pregnant Swedish women		5			TEE (MJ d^{-1})	TEE$_{\text{IDEEA}}$	0.66		1.0 ± 2.2	
					AEE (MJ d^{-1})	AEE$_{\text{IDEEA}}$	0.44			
41 Japanese adults (12 males)	Lifecorder		14	BMR$_M$	PAL	AC$_{\text{all subjects}}$	0.06^{NS}			(59)
						AC$_{\text{males}}$	0.64			
						AC$_{\text{females}}$	0.08^{NS}			
56 adults ≥65 years	New Lifestyles pedometer	7	10	RMR$_M$	AEE (MJ d^{-1})	AEE$_{\text{SWA}}$	0.48		1.67 ± 2.02	(28)
						Steps$_{\text{SWA}}$	0.56			
	Actigraph	10				AC$_{\text{Actigraph}}$	0.56			
	SenseWear	10				Steps$_{\text{Actigraph}}$	0.59			
						Steps$_{\text{Pedometer}}$	0.53			
						AEE$_{\text{Actigraph Crouter}}$	0.60		−1.43 ± 2.14	
						AEE$_{\text{Actigraph Freedson}}$	0.49		0.52 ± 1.75	
					AEE$_{\text{adj}}$	Steps$_{\text{SWA}}$	0.60			
						AC$_{\text{Actigraph}}$	0.58			
						Steps$_{\text{Actigraph}}$	0.62			
						Steps$_{\text{Pedometer}}$	0.59			
					AEE (kJ kg^{-1} d^{-1})	Steps$_{\text{SWA}}$	0.59			
						AC$_{\text{Actigraph}}$	0.56			
						Steps$_{\text{Actigraph}}$	0.63			
						Steps$_{\text{Pedometer}}$	0.60			
66 boys (5–15 years)	RT3	4	14	BMR$_M$	TEE (MJ d^{-1})	TEE$_{\text{RT3}}$	0.61		1.50 ± NP	(29)
13 overweight/obese	RT3	14	14	BMR$_{C\&M}$	AEE (MJ d^{-1})	AEE$_{\text{RT3}}$	0.55			(30)
						AEE$_{\text{RT3 with BMR measured}}$	0.67		0.50 ± 1.11	
	Tritrac-R3D					AEE$_{\text{Tritrac-R3D}}$	NS			
						AEE$_{\text{Tritrac-R3D with BMR measured}}$	0.36^{NS}		0.62 ± 3.09	

Table 2 *Continued*

Subjects	Accelerometer	*N* days accelerometry	*N* days DLW	BMR (Measured or Calculated)	Dependent variable	Independent variables (non-significant variables included in the model are indicated with NS)	*R*	PR or RI	Difference DLW-accelerometer (mean ± 2 SD)	Ref
36 adults	RT3	14	15	RMR_M	TEE (kJ d^{-1})	AC	0.32			(36)
						Gender, FM, FFM, RMR, AC	0.82	0.21 (PR)		
						TEE_{RT3}			539 ± 4,100*	
					TEE (kJ kg^{-1} d^{-1})	Gender, FM, RMR, AC	0.81	0.21 (PR)		
					AEE (kJ d^{-1})	AEE_{RT3}			485 ± 4,000*	
					AEE (kJ kg^{-1} d^{-1})	Gender, FFM, FM, AC	0.73	0.27 (PR)		
30 healthy adults	SenseWear Pro3 (right arm)	14	14	RMR_C	TEE (MJ d^{-1})	TEE_{SWA}	0.82		0.47 ± 2.72	(25)
					AEE (MJ d^{-1})	AEE_{SWA}	0.71		0.51 ± 2.33	
	SenseWear Mini (left arm)				TEE (MJ d^{-1})	TEE_{Mini}	0.84		0.09 ± 2.59	
					AEE (MJ d^{-1})	AEE_{Mini}	0.69		0.50 ± 2.39	
7 critically ill children	Tracmor	6	6	RMR_M	AEE (kJ kg^{-1} d^{-1})	AC	0.85			(38)
10 monozygotic twin pairs (25 years)	Tracmor	7	14	BMR_M	AEE (kJ d^{-1})	AC	0.68			(37)
					AEE (kJ kg^{-1} d^{-1})	AC	0.79			
					PAL	AC	0.62			
15 healthy adults	Tracmor				PAL	AC	0.68			(42)
						$MET_{from\ accel}$	0.71			
30 adults	$Tracmor_D$				TEE (MJ d^{-1})	SMR, AC	0.87	0.46 (PR)		(32)
						BM, AC	0.73	0.48 (PR)		
						FFM, AC	0.82	0.41 (PR)		
					AEE (MJ d^{-1})	BM, AC	0.68	0.55 (PR)		
						FFM, AC	0.73	0.48 (PR)		
					AEE (MJ kg^{-1} d^{-1})	AC	0.71			
					PAL	AC	0.68			

For consistency, R^2 values were transformed into *R* values where necessary; kcal was transformed into kJ or MJ where necessary. As a consequence, numbers may be subject to small rounding errors.

*The limits of agreement were only provided graphically in a Bland–Altman plot and may thus deviate slightly from the exact number.

†The mean bias was calculated from a cross-validation (in the same sample) of the generated regression equations using the jackknife approach (leave one out). Predictions were generated with an equation from all individuals except for one whom an estimate was generated, and then this was repeated for all individuals (35).

AC, activity counts from the accelerometer. The calculation of activity counts can differ between monitors and is often company proprietary information; ACC, acceleration; AEE_{adj}, residuals of AEE regressed on body weight; AEE HR_{flex}, activity-related energy expenditure calculated using the flex heart rate method; AEE, activity-related energy expenditure; AR_{new}, calculated using the new ActiReg algorithm; AR_{old}, calculated using the original ActiReg algorithm; BM, body mass; BMR, basal metabolic rate; CCC, Lin's concordance correlation coefficient; CSTS, cross-sectional time series; DLW, doubly labelled water; FFM, fat-free mass; FM, fat mass; MARS, multivariate adaptive regression splines; MET, metabolic equivalent (MET = total EE/resting EE); MVPA, minutes spent in moderate-to-vigorous physical activity; NP, not provided; NS, non-significant; PAL, physical activity level; PAL_{adj}, residuals of TEE regressed on RMR; PR, partial *R*; RI, *R* increase; RMR, resting metabolic rate; SMR, sleeping metabolic rate; SWA, SenseWear Armband; TEE, total energy expenditure; TEE_{LPF}, a low-pass five-point median filter (LPF) to remove transient artefacts was applied to the EE estimation; TEE_{LPF}, total energy expenditure estimation after applying a low-pass five-point median filter; TEE_{RT3}, based on measured BMR and AEE from RT3 (calculation not provided); TEE_{SWA} and TEE_{Mini}, total energy expenditure from the SenseWear and SenseWear Mini, calculated by entering age, gender, height and weight.

assessment period to derive a value in MET.hours (h) that reflects overall free-living EE (26). The GENEA is a triaxial seismic acceleration sensor (STMicroelectronics, Geneva, Switzerland). It can be easily worn at multiple locations on the body (e.g. wrist, waist, ankle). The GENEA has 500 MB of memory and can store ~8 d of data in raw mode (at 80 Hz). Users have the ability to select user-defined sample frequencies ranging from 10 to 80 Hz (27). The New Lifestyles pedometer (NL-2000, New-Lifestyles, Inc., Lee's Summit, MO, USA) is a pedometer with a 7-d memory and was used to monitor steps per day, worn on the left hand side of a waist-worn elastic belt (28). The RT3 (Stayhealthy, Inc., Monrovia, CA, USA) is a triaxial piezo-resistive accelerometer. Physical activity related energy expenditure is derived from the magnitude of the vectors of the three axes (x-, y- and z-axis) using the RT3 software package. Subject's characteristics (weight, height, age, gender) are entered when the monitor is initialized (29,30). The Intelligent Device for Energy Expenditure and Activity (IDEEA, Minisun, Fresno, CA, USA) consists of five small sensors (each $16 \times 14 \times 4$ mm, approximately the size of a small postage stamp) that are attached to the body and by flexible cables to a small 200-g data collection device (microcomputer) that can be worn on the belt. The basic working principle of an IDEEA is the following: the IDEEA system monitors body and limb motions constantly through five sensors attached to the chest, thighs and feet. The different combinations of signals from those five sensors represent different physical activities, which are coded as 32 different numbers for 32 activities (31). The Tracmor$_D$ (Philips New-Wellness Solutions, Eindhoven, the Netherlands) was based on the research device Tracmor (2,6). The device is a small, lightweight instrument that is waterproof up to 30 m depth, and has a battery life of 3 weeks and an internal memory that can store data for up to 22 weeks (32). The Actigraph/CSA/MTI (first known as CSA, Computer Science Applications model 7164; later known as MTI, Manufacturing Technology Incorporated, Fort Walton Beach, FL, USA; now known as Actigraph) is one of the most validated and used activity monitors in the literature. It was a small, lightweight, uniaxial accelerometer detecting accelerations from 0.05 to 2 g. In the mid-2000s Actigraph replaced the model AM7164 by the GT1M and with that switched from a piezoelectric to a capacitive sensor (33). In 2009, Actigraph released the model GT3X, their first triaxial accelerometer (33). At the time of this review, a DLW validation of this model was not yet available.

Accelerometer validity

Table 2 summarizes the results from all validation studies, including the population studied, the dependent variables used, correlations and partial correlations when available, and mean differences between DLW-derived EE and the accelerometer. The dependent variables used are total energy expenditure (TEE), activity-related energy expenditure (AEE) or physical activity level (PAL). Independent variables vary between studies, but accelerometer output is most commonly expressed as 'activity counts'. Some studies only mentioned calculated EE based on activity monitor output and subjects' characteristics. Other studies report independent variables such as minutes spent in moderate to vigorous physical activity (Actigraph) or time spent upright (ActivPAL).

When the independent variables are activity counts and/or subject characteristics, the study usually mentions correlations (and in some cases a partial R or R increase). From these studies, a new prediction equation can be developed when the regression coefficients are provided. When a mean difference between DLW-derived and accelerometer-derived TEE or AEE is provided, the prediction equation was previously developed in a different sample (sometimes a proprietary equation included in the activity monitor). There are two exceptions. In the studies of Assah *et al.* (34) and Corder *et al.* (35), the equation was developed in a certain sample and cross-validated in the same sample using the jackknife (leave-one-out) approach. Hence, these two studies mention the correlations with the independent variables (e.g. activity counts, body mass, gender) as well as a mean difference (±2 SD). Mean differences in TEE or AEE between DLW and the accelerometer were often small on the group level, but the limits of agreement (±2 SD) were usually large.

The most validated accelerometer was the Actigraph, followed by the Tracmor. Observed correlations between PAL and activity counts vary between 0.06 (Lifecorder) and 0.68 (Tracmor$_D$). Interpreting correlations between AEE or TEE and activity counts becomes more difficult as body mass and other characteristics are the main determinants of EE. Thus, a partial correlation or an R increase is needed. This was only reported in three studies (19,32,36). Output from the 3dNX accelerometer significantly increased the prediction of TEE in addition to fat-free mass (FFM) (19). The Tracmor significantly contributed to the prediction of TEE after correcting for sleeping metabolic rate, body mass or FFM (32). Likewise, the RT3 significantly contributed to the prediction of TEE and AEE after correction for subject characteristics. When AEE is expressed per kg body mass, correlations with activity counts vary between 0.37 (Actigraph) (34) and 0.79 (Tracmor) (37) or even 0.85 (Tracmor), but the latter was in a small population of seven critically ill children (38).

Discussion

The aim of the current paper was to review all recent validation studies of accelerometers against DLW in order to guide researchers in their selection of an appropriate accelerometer for a specified research goal. Tables 1 and 2 show the large variability in types of accelerometers, how accelerometer output is provided, and their validity to assess daily physical activities.

Where DLW provides an average measure of EE over a period of 1–3 weeks, accelerometers capture actual body movement and are able to provide more detailed information about the physical activity pattern. Advancements in sensor technologies have caused a rapid development of different accelerometer types with different sensor specifications (Table 1). The result is a vast amount of available literature on accelerometers, sometimes with unsupported (commercial) validity claims.

Activity type monitoring

One of the most noticeable developments over recent years is the evolution to using more piezo-resistive and capacitive sensors. Given that piezoelectric sensors do not respond to static acceleration, i.e. unable to detect the field of gravity, these can not be used to identify body postures such as lying or standing. Piezo-resistive or capacitive sensors measure the gravitational field as 1 g, and hence the output of the sensor is related to posture. These types of sensors are able to provide additional information on activity types. The best wearing position for an accelerometer to assess daily life physical activity is as close as possible to the centre of mass, hence the lower back or hip. Using a single accelerometer placed at the lower back, Bonomi *et al.* were able to identify six different activity types, i.e. lying, sitting/standing, active standing, walking, running and cycling. Only the differentiation between standing and sitting could not be achieved with a single accelerometer at this position (39). Multiple sensor systems, such as the IDEEA monitor, can solve this problem, but greatly reduce wear ability and practicality and failure rate can be high. As a consequence, monitoring over longer periods of time becomes difficult (31,40). The ActivPAL, attached to the upper side of the thigh using an adhesive dual layer hydrogel, is also capable of differentiating between sitting, standing and walking.

The interest in identifying postures and activity types may be partly inducted by literature showing the health risk of sedentary behaviour, independent of the physical activity level (3,4,41). Accurate identification of, for example, sitting behaviour may lead to a better prediction of certain cardio-metabolic and inflammatory outcomes than physical activity alone. In addition, Bonomi *et al.* showed that identification of activity types led to a better estimation of daily EE than just using activity counts (42).

Accelerometer's technical specifications and computational methods

Table 1 shows, when provided by the manufacturer, more detailed information about the frequency response, sampling time and dynamic range of the different accelerometers. This is essential information because selection of the correct frequency range and amplitude will considerably reduce 'noise' as a consequence of those accelerations not arising from human movement but from external sources such as vehicles (1). Already in 1985, it was demonstrated that 99% of the acceleration power in gait is concentrated below 15 Hz (43). The frequency range of daily activities, performed on a force platform, was shown to be between 0.3 and 3.5 Hz (44). For an accelerometer worn at the waist level, an amplitude range of −6 to +6 g will suffice (1). Unfortunately, most manufacturers do not provide the specifications of the accelerometers. In addition, low- and high-pass frequency filters are often used to limit the frequency response within specific boundaries. Most devices contain proprietary formulas to calculate activity counts and/or EE. The consequence is that data, such as activity counts, are not comparable between devices, and hence between studies. Other commonly used outcome measures such as time spent in moderate physical activity are also not uniformly comparable between devices because there is no consensus on accelerometer cut-off points. Generally accepted are the cut-off points of <3 MET for low intensity, 3–6 MET for moderate intensity, and 6 MET or more for vigorous intensity. The difficulty, however, is to accurately translate activity monitor output to the correct METs. With the collection of raw data and the use of accelerometers sensitive to static acceleration, the signal could also be expressed as a common metric such as acceleration relative to the local acceleration due to gravity (g). Even then, validity of the accelerometer in daily life can only be tested against an independent technique, such as DLW, as the recorded 'g forces' do not necessarily arise from human movement and can be dependent on the dynamic range of the accelerometer. A dynamic range that is too narrow may saturate the acceleration signal during high-intensity movement. Heil recently published recommendations for collecting, processing and reporting physical activity data collected with accelerometers (45). As potential physical activity outcomes, movement, time, EE and activity type-based variables were suggested. All of these could indeed be seen as a relevant health outcome, but the prerequisite is that the monitor used provides accurate data on these variables. For example, time spent in moderate physical activity is highly dependent on the cut-off points used, which vary between and even within accelerometers depending on the study referred to (46). Again, the problem arises that no independent validation technique is available to validate these outcomes in daily life. For example, there is no good reference technique available to assess 'activity types' in daily life, except for direct observation that is not feasible over longer periods of time and without affecting activity behaviour. Obviously, extensive laboratory testing, mimicking conditions of daily life, can greatly contribute to validity testing of the accelerometer.

The importance of doubly labelled water measurements

Not all researchers agree that DLW is the best technique to validate accelerometers as it provides a measure of EE and not movement. Undoubtedly, both techniques have their own (dis)advantages and can be used complementarily. Where an accelerometer can provide a day-to-day profile of physical activity, DLW provides a measure of TEE over 7–14 d. Clearly, body movement does not equal EE, but by definition body movement will always result in EE. Therefore, DLW is an accurate and independent technique to assess the validity of motion sensors in daily life. Obviously, like all analytical techniques, DLW measurements are prone to error. The difference in DLW-assessed TEE compared to TEE as measured in a respiration chamber was 0 ± 6% (mean ± SD) in our laboratories (47), which was in agreement with data from Schoeller *et al*. (1 ± 7%) (48). When AEE is used as the dependent variable, the accuracy depends on the correct measurement of TEE, basal metabolic rate (BMR) and diet-induced thermogenesis (DIT). When BMR is calculated instead of measured, the accuracy of calculated AEE will be affected. DIT is mainly determined by the energy content and the protein fraction of the food and is on average 10% of TEE for subjects in energy balance, consuming a mixed diet (49).

Those accelerometers that contain proprietary formulas to calculate EE have the major disadvantage that the contribution of accelerometer output to the explained variation is unknown. It then becomes impossible for researchers to evaluate whether the accelerometer has any added value to a simple prediction of EE by using just body mass, height, gender and age. Table 2 shows that many of the accelerometers tested perform badly when compared to DLW-assessed EE. When estimates of EE from the accelerometer are correlated with EE from DLW, most of the explained variations will arise from subject characteristics. As previously shown, subject characteristics alone can already explain 64% of the variation in total EE in a population of healthy subjects (2).

Addition of extra sensors

Some researchers have investigated the effect of adding other physiological measures to the acceleration signal to become more accurate predictions of EE. The SenseWear also measures skin temperature, galvanic skin response, and heat flux, and the Actiheart includes HR monitoring in addition to accelerometry. So far, this has not resulted in improvements in estimating EE. In the study of Colbert *et al*. (Table 2), AEE, as predicted by the SenseWear, showed a lower correlation with DLW-assessed AEE than only the steps from the SenseWear. In this case, the proprietary algorithm uses subject characteristics and input from different sensors (heat flux, skin temperature, galvanic skin response, accelerometer) which results in a worse correlation than using just 'steps' from the accelerometer (28). Furthermore, disadvantages of multiple sensor systems are that each sensor will have its inherent measurement error, that the risk of technical failure will increase, and wear ability will decrease.

How to choose an accelerometer

The choice of the most suitable accelerometer will depend on the research goal, the population being studied, the preferred outcome measures and the available budget. There is not a single accelerometer that can fulfil all requirements. If there is a need to differentiate between not just physical activity intensity but also activity type or postures, then a piezo-resistive or capacitive sensor is needed. These sensors will need the battery power and storage capacity for raw data collection over several days. Physical activity monitoring needs to be done over several days in order to get a good representation about the habitual physical activity pattern. In the elderly, it was shown that at least 3 d was necessary (50). In younger subjects, activity patterns often vary more substantially and a full week of monitoring may be advisable. Activity type recognition is hard to validate under daily life conditions, hence extensive laboratory validation is necessary. In addition, behaviour profiling usually becomes technically challenging when raw data over several days need to be processed. In specific situations, a multiple sensor system (such as the IDEEA) could be useful, allowing more extensive differentiation between different postures and/or activity types. For daily life, these systems are generally less suitable.

To assess daily life physical activities, validation against DLW is necessary. Ideally, the observation period is then the same for the accelerometer and DLW, which is not always the case in the studies included in Table 2. Even when no specific information about EE is required, the validation against DLW indicates whether the accelerometer has really captured body movement. When no relation between accelerometer output and EE is present, by definition the accelerometer has not properly measured physical activity.

Conclusion

In conclusion, an increasing number of accelerometers have been validated under free-living conditions. Performance of an accelerometer is best evaluated when the contribution of the accelerometer output itself (and any additional physiological data) is reported, independent of subject characteristics. The ability to store raw acceleration data further improves the possibility for more advanced data analysis by the researcher. Activity recognition has great potential to improve the assessment of physical activity-related health outcomes. So far, there is little evidence that adding other physiological measures such as HR significantly improves the estimation of EE.

Conflict of interest statement

There are no conflicts of interest.

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